Given:

- plotData.m
- plotDecisionBoundary

Lab 03 LogisticReg Lin.m

```
%% Machine Learning
   % Lab 3: Logistic Regression (Linear case)
   % —— Admit students to university -
   %{
 4
 5 \mid In this part of the exercise, you will build a logistic regression model to
   predict whether a student gets admitted into a university.
   Suppose that you are the administrator of a university department and
   you want to determine each applicant's chance of admission based on their
   results on two exams. You have historical data from previous applicants
9
10\, |that you can use as a training set for logistic regression. For each training
   example, you have the applicant's scores on two exams and the admissions
   decision.
   %}
13
14
   % Initialization
16
   clear ; close all; clc
17
18 | % Load Data
19 % The first two columns contains the exam scores and the third column
20 % contains the label.
21
   %Data parsing
22
   data = load('ex2data1.txt');
   X = data(:, [1, 2]); % x1: exam 1 point; x2: exam 2 point
25
   Y = data(:, 3);
                       % Passed or Failed
26
   % Print out some data points
   fprintf('First 10 examples from the dataset: \n');
29
   fprintf(' x = [\%.0f \%.0f], y = \%.0f \n', [X(1:10,:) Y(1:10,:)]');
30
31
   %% Plotting
   % We start the exercise by first plotting the data to understand the
33
   % the problem we are working with.
34
35 | fprintf(['Plotting data with + indicating (y = 1) examples and o ' ...
36
             'indicating (y = 0) examples.\n']);
37
38 plotData(X, Y);
   % Put some labels
40 hold on;
41 % Labels and Legend
42 | xlabel('Exam 1 score')
43 | ylabel('Exam 2 score')
   % Specified in plot order
   legend('Admitted', 'Not admitted')
46
   hold off;
47
48 | % Compute Cost and Gradient
49 % m: number of samples
50 % n: number of features
51 \mid [m, n] = size(X);
52 \mid% Additional Bias
```

```
X = [ones(m, 1) X];
54
    % Initialize Weights
56 \mid initial_w = zeros(n + 1, 1);
57
58
    % Compute and display initial cost and gradient
59
    [C, grad] = costFunction(initial_w, X, Y);
60
61 | fprintf('Cost at initial weights (zeros): %f\n', C);
    fprintf('Expected cost (approx): 0.693\n');
63 | fprintf('Gradient at initial weights (zeros): \n');
    fprintf(' %f \n', grad);
65
    fprintf('Expected gradients (approx):n - 0.1000 n - 12.0092 n - 11.2628 n');
67
    % Compute and display cost and gradient with non—zero theta
68
    test_w = [-24; 0.2; 0.2];
69
    [C, grad] = costFunction(test_w, X, Y);
 70
 71
    fprintf('\nCost at test weights: %f\n', C);
 72
    fprintf('Expected cost (approx): 0.218\n');
    fprintf('Gradient at test weights: \n');
 74
    fprintf(' %f \n', grad);
    fprintf('Expected gradients (approx):\n 0.043\n 2.566\n 2.647\n');
 75
 76
 77
    %% === Optimizing using fminunc ===
 78
 79
    % In this exercise, you will use a built—in function (fminunc) to find the
 80
    % optimal parameters weights.
 81
82
    % Set options for fminunc
83 options = optimset('GradObj', 'on', 'MaxIter', 400);
84
85 % Run fminunc to obtain the optimal theta
 86 % This function will return weights and the cost
87
    [w, C] = fminunc(@(t)(costFunction(t, X, Y)), initial_w, options);
 88
    % Print weights to screen
    fprintf('Cost at weights found by fminunc: %f\n', C);
    fprintf('Expected cost (approx): 0.203\n');
92 | fprintf('weights: \n');
93 | fprintf(' %f \n', w);
    fprintf('Expected weights (approx):\n');
95
    fprintf(' -25.161\n 0.206\n 0.201\n');
96
    %% Plot Boundary
97
98
    plotDecisionBoundary(w, X, Y);
99
100 |% Put some labels
101 hold on;
102
    % Labels and Legend
103
    xlabel('Exam 1 score')
104
    ylabel('Exam 2 score')
105
106 | % Specified in plot order
107
    legend('Admitted', 'Not admitted')
108 hold off;
109
```

```
110 | % ======= Part 4: Predict and Accuracies ========
111 |% After learning the parameters, you'll like to use it to predict the outcomes
112 \ on unseen data. In this part, you will use the logistic regression model
113 \mid% to predict the probability that a student with score 45 on exam 1 and
114
    % score 85 on exam 2 will be admitted.
115
116
    % Furthermore, you will compute the training and test set accuracies of
117
    % our model.
118
119
    prob = sigmoid([1 45 85] * w);
120 | fprintf(['For a student with scores 45 and 85, we predict an admission ' ...
121
             'probability of %f\n'], prob);
122
    fprintf('Expected value: 0.775 +/- 0.002\n\n');
123
124
    % Compute accuracy on our training set
125
    p = predict(w, X);
126
127
    fprintf('Train Accuracy: f^n, mean(double(p == Y)) * 100);
128
    fprintf('Expected accuracy (approx): 89.0\n');
129
    fprintf('\n');
```

sigmoid.m

```
function g = sigmoid(z)
%SIGMOID Compute sigmoid function
g = zeros(size(z));
g = 1 ./ (1 + exp(-z));
end
```

costFunction.m

```
1 | function [C, grad] = costFunction(w, X, Y)
   %COSTFUNCTION Compute cost and gradient for logistic regression
3
   % Initialize some useful values
4 | m = length(Y); % number of training examples
5
   C = 0;
6
   grad = zeros(size(w));
   C = (1/m) * sum((-Y).*(log(sigmoid(X*w))) - (1-Y).*(log(1-sigmoid(X*w))));
9
10 | for i=1:size(w)
11
    grad(i) = (1/m) * sum((sigmoid(X*w)-Y).*X(:,i));
12 end
13
   end
```

predict.m

```
function p = predict(w, X)
   %PREDICT Predict whether the label is 0 or 1 using learned logistic
   m = size(X, 1); % Number of training examples
   p = zeros(m, 1);
5
6
   temp = sigmoid(X*w);
   for i=1:m
8
     if temp(i) >= 0.5
9
       temp(i) = 1;
    else
       temp(i) = 0;
11
12
    end
13 end
14
   p = temp;
   end
```